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Temporal Pattern Models for Physiological Arousal During a Steering Task

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Abstract

Physiological arousal can be a signal of attention, reflecting predictability and significance of stimuli or events. We explored temporal patterns in task-related physiological arousal and their connection to performance in repeated trials of a visuomotor steering task. Participants (N = 9) played a total of forty trials of a high-speed steering task in eight sessions over a period of 2-3 weeks. Temporal changes in electrodermal activity during task performance were modelled as habituation, and connections between performance, perceived importance and individual differences in habituation rate were examined. Additionally, within-subject changes in habituation were compared to deviations from predicted performance. We found that sustained task-related arousal (slow habituation) was connected to better performance both between groups and within participants. Slow habituation was also related to higher subjective reports of perceived importance. Taken together, these results suggest that temporal changes in task-related arousal during learning are related to the processing of task-relevant cues and may reflect motivational states that direct selective attention.

Keywords: habituation; learning; performance; electrodermal activity

Introduction

Physiological arousal is a marker of attentional processing, signalling the predictability and significance of stimuli, and reflecting motivation (Bradley, 2009). Studying *temporal patterns* in physiological arousal during learning, in a longitudinal design, can shed light on some of the elemental processes involved in learning and selective attention: here, we studied habituation and motivation. We did this by modelling patterns in electrodermal activity (EDA) during repeated performance in a novel task and analysing them with respect to behavioural measures of learning and self-reports of perceived importance (abbreviated as PI). The task used in our experiment was a high-speed steering task, and learning in the task has previously been found to fit well with a power law learning curve (Cowley et al., 2019). Based on these findings, it is interesting to investigate arousal and learning in a longitudinal design, which allows for a consideration of the dynamic interactions underlying attention, learning and performance.

We investigate whether the patterns of physiological arousal – measured by EDA – during repeated task performance follow the characteristics of habituation outlined by Grissom and Bhatnagar (2009), comprising four key themes. First, habituation is seen as a *decline in responses to repeated stimuli*. Second, it is reversible, meaning that a response can re-occur if stimulation is withheld (*spontaneous recovery*). Third, it is affected by frequency of stimulation: the more frequent the stimulation, the more rapid the habituation rate (*potentiation of habituation*). Fourth, habituation can *progress beyond resting (baseline) levels*. Note that only the criteria applicable in our context are reviewed (e.g. dishabituation by another stimulus and habituating stimulus strength are excluded).

Habituation is related to increasing predictability of stimuli and is therefore a form of learning (Balkenius, 2000). Repeated occurrences bring less additional information and need not be attended to, unless the stimulus is perceived as important (Bradley, 2009). Orienting responses observed in EDA also manifest action preparation with respect to salient (unpredictable or significant) stimuli, reflecting the role of the sympathetic nervous system in mobilising resources (Bradley, 2009). Habituation of task-related arousal could therefore signal increased prediction accuracy of expectations – i.e. learning – in the task, but also perceived importance of the task.

Our research questions are:

RQ1 Do the changes in task-related arousal during multiple trials of a steering task follow the criteria for habituation (Grissom & Bhatnagar, 2009)?

RQ2 Are between-participant differences in habituation rate, or within-participant changes in habituation, related to task performance or PI?

a Are there differences in performance or PI between groups based on habituation rate?

b Are deviations from predicted performance connected to habituation within participants?

Methods

Participants

Nine participants (3F, 6M, 22-38 years old) were recruited, and they gave signed informed consent before participating. The study followed guidelines of the Declaration of Helsinki and was approved by the University of Helsinki Ethical review board in humanities and social and behavioural sciences (statement 31/2017; study title MulSimCoLab).

Design

Participants played a total of forty 2-4 minute trials of a high-speed visuomotor steering task in eight sessions over a period of 2-3 weeks. EDA during baseline and task was recorded in five sessions (1 and 5-8). (Heart rate and eye-tracking data were also recorded in these sessions but are not reported here.)

In sessions 1 and 5-8, a baseline measurement of five minutes was recorded, where participants sat still while looking at a dark blue screen. Each participant then played five trials of the task. After each trial, participants filled in a self-report questionnaire, the Flow Short Scale (FSS; Engeser & Rheinberg, 2008).

Materials

Task The task was a custom high-speed visuomotor steering task (*CogCarSim*, code available at https://doi.org/10.6084/m9.figshare.7269467), where the participant steered a forward-moving cube along a bounded track, avoiding randomly placed stationary obstacles. Velocity increased at a constant rate if there were no collisions and dropped if obstacles were hit. Trial duration therefore signalled performance.

Equipment The game was played on a computer with a 55'' screen (LG 55UF85, 1920 x 1080 pixels) running Windows 10. Participants used a Logitech G920 Driving Force steering wheel and sat on a Playseat Evolution Alcantara driving seat (Playseats B.V., The Netherlands), aligned to the horizontal midpoint of the screen, at 90-120 cm from eye to screen.

EDA data was recorded at 128 Hz sampling rate using NeXus-10 (Mind Media B.V, Roermond-Herten, The Netherlands) and encoded using Trusas software (https://github.com/jampekka/trusas-nexus) running on a Debian GNU/Linux 9 OS laptop.

Electrodermal activity Ag-AgCl electrodes were attached to the medial-plantar surface of the left foot. The plantar site was used instead of the palmar site to minimise movement artefacts due to steering control.

Flow Short Scale PI was measured with three items of the FSS questionnaire, translated into Finnish (Cowley et al., 2019). The items were: *'Something important to me is at stake here'*, *'I must not make any mistakes here'*, and *'I am worried about failing'*. Participants responded on a 7-point Likert scale (1 = *not at all*, 4 = *partly*, 7 = *very much*). Cronbach's alpha was .73.

The FSS also included ten items measuring flow experience, and three items on perceived fit of demands and skills; not reported here as they do not relate to our research questions (see Cowley et al., 2019 for a report on flow and performance).

Data processing

EDA was processed with MATLAB (MathWorks, Natick, MA, US) using the Ledalab 3.4.9 toolbox (http://www.ledalab.de). The signal was downsampled to 10 Hz and decomposed into tonic and phasic components using Continuous Deconvolution Analysis (CDA; Benedek & Kaernbach, 2010). Skin conductance responses (SCRs) were detected using a threshold of 0.05 µS. SCR frequency per minute was computed as our primary EDA feature. Because EDA can vary considerably between sessions due to, for example, differences in electrode contact from session to session, SCR frequency during baseline was subtracted from SCR frequency during trial.

Data from 13 trials (5.8 %) was omitted due to missing or low-quality data. For session baselines, the first and last minute from each five-minute recording were omitted due to a large number of artefacts in those periods, resulting in three-minute baselines.

Statistical methods

Statistical analyses were conducted with R (version 3.5.1). Linear mixed models (LMMs) were used for the habituation model (RQ1), as well as power-law learning curves and within-participant analysis of habituation and performance (RQ2b). LMMs were fitted with the *lme4* R package using maximum likelihood. The *lmerTest* package was used to obtain *p* values; degrees of freedom were approximated with Satterthwaite's method. Linear regression was used for RQ2a. All *p* values were adjusted for multiple comparisons using Bonferroni-Holm.

Habituation of SCR frequencies (RQ1) was modelled using log(trial) as a fixed effect predictor, and participant and session as random effect predictors. Both random intercept and random slope were included to allow for variation between participants and sessions. To study the potentiation of habituation criterion for RQ1, a similar model was used but session was a fixed effect predictor instead of random.

For RQ2a, to look at differences in performance and PI between groups based on habituation rate, participants were classified as slow (n = 5) or fast (n = 4) habituators, based on participant-level random slope coefficients of the habituation model for RQ1.

For RQ2b, trial-level difference scores were used to explore habituation and deviations from predicted performance within participants, with random effect of participant (intercept and slope). Performance was predicted with a power-law learning curve (Newell & Rosenbloom, 1981).

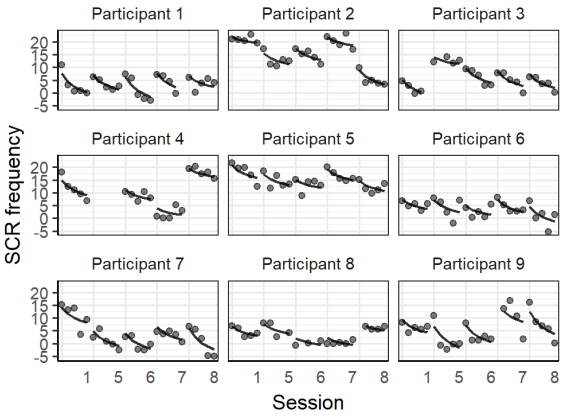

Figure 1: SCR frequencies for trials 1-5 (back-transformed from logarithmic scale) of sessions 1 and 5-8. Lines represent the LMM fit.

Results

RQ1. Habituation Model

The frequency of SCRs ranged from 0 to 15 per minute (M = 3.9, SD = 4.1) during baseline, and from 0 to 23.62 per minute (M = 11.2, SD = 6.1) during trials (before baseline was removed).

Decline in responses Trial number affected SCR frequency negatively on a log-linear scale (b = -3.03, SE = 0.44, p < .001), meaning that physiological responses habituated with increasing trials (Figure 1). For example, from trial 1 to 2, the predicted decrease in SCR frequency was 2.1 units. Negative random slopes for all nine participants and 44 sessions indicate that habituation occurred in every session. Comparison to a null model implied that variance explained by the two models was different (χ^2 = 16.4, p < .001); log(trial) improved the explanatory power of the model. Akaike information criterion (AIC) for the full model was 1127 compared to 1142 for the null model.

Spontaneous recovery There was spontaneous recovery in SCR frequencies between sessions. Change in SCR frequency between the last and first trials of consecutive sessions (5-8) was mostly positive (M = 4.08, SD = 6.31) indicating recovery of habituation between sessions (t(29) = 3.54, p < .001).

Potentiation of habituation When SCR frequency was predicted by session number and log(trial), there was some indication of a main effect of session (b = -0.38, SE = 0.18, p = .08), but no interaction effect between log(trial) and session was found, i.e. there was no clear pattern in the rate of habituation within sessions. Time between sessions had no effect on SCR frequency or habituation rate.

Progression below baseline In 20 trials (9 %), SCR frequency during trial was below baseline. Most trials (18) were in sessions 5-8, and 14 in trials 4 or 5.

RQ2. Habituation, Performance and PI

Learning curves Trial duration was lower with increasing trial number on a log-log scale (b = -0.07, SE = 0.006, p < .001), indicating that all participants improved their performance over cumulative trials. The slopes and intercepts of the learning curves were very strongly correlated (r(7) = -0.99, p < .001).

RQ2a. Between groups Having slow habituation rate corresponded to better performance (b = -0.03, SE = 0.007, p < .001), when added as a predictor in a power-law model where log(duration) was the dependent variable and log(cumulative trial) was the independent variable. The model explained 43% of variance in performance. Figure 2 shows the learning curves for both groups.

PI ranged between 1.33 and 6.00 (M = 3.77, SD = 1.14). There were differences between habituation groups when analysed with linear regression with cumulative trial as a control variable, the effect of which was not significant. Average PI was 4.31 (SD = 0.75) for the slow habituation group and 3.10 (SD = 1.19) for the fast habituation group (t(357) = 7.63, p < .001, model R^2 = .14).

RQ2b. Within participants Slow habituation was linked to better-than expected performance within participants. Average trial-level habituation scores

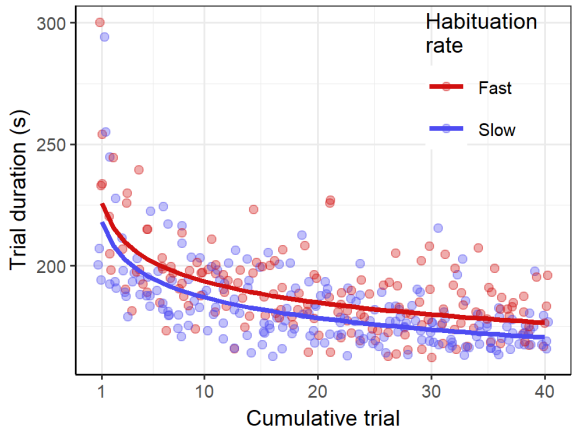

Figure 2: Duration predicted by cumulative trial and habituation group with linear regression. Both axes back-transformed from logarithmic scale.

(SCR frequency during trial – SCR frequency during previous trial) were -1.82 (SD = 3.22) for the fast habituation group and -0.90 (SD = 3.09) for the slow habituation group.

Deviation scores were residuals of the learning curve model above. They were weakly correlated with trial-level habituation scores ($r(162) = -0.25$, $p = .004$), meaning that negative deviation scores (better-than-predicted performance) was connected to slower habituation. A similar relationship was seen in a LMM with trial-level habituation as dependent variable, and trial (1-5) and deviation score as independent variables (Table 1). Comparison to a null model indicated that deviation score explained significantly more variance than the null model without that predictor ($\chi^2 = 11.1$, $p = .001$); AIC of the full model was 836 while AIC of the null model was 845.

Table 1: LMM results of habituation score predicted by trial and deviation score, with random participant effect for trial (intercept and slope)

	b	SE	t
Intercept	-3.75***	0.81	-4.62
Trial	0.67*	0.23	2.96
Deviation score	-20.35**	6.00	-3.39

*** $p < .001$, ** $p < .01$, * $p < .05$

Discussion

For **RQ1**, task-related arousal decreased for all participants in nearly all sessions, indicating that a habituation model was successful in capturing changes in arousal in a task situation. Spontaneous recovery occurred between sessions, and some SCR frequencies progressed below baseline levels, mostly in later sessions and trials. However, there was no clear pattern in habituation slopes between sessions, and it cannot be inferred whether potentiation of habituation occurred.

All participants improved performance across cumulative trials. This suggests that the observed habituation patterns may be associated with learning effects. Sustained task-related arousal (slow habituation) was connected to better performance both between groups (**RQ2a**) and within individuals (**RQ2b**). Slow habituation was also related to higher subjective reports of PI, in line with previous research, which has linked maintained arousal to high significance of stimuli (Bradley, 2009). Taken together, these results suggest that temporal changes in task-related arousal during learning are related to processing of task-relevant cues, and may reflect learning effects and motivational states directing selective attention.

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